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Statement by the Candidate

I wish to state that the work embodied in this synopsis titled "An Enhanced Deep Ensemble Prediction and Recommendation Framework for Depression Risk Detection" forms my own contribution to the work carried out under the guidance of Dr. Bhavesh Patel at the Shah and Anchor Kutchhi Engineering College. I declare that this written submission represents my ideas in my own words and where others ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission.

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1 Introduction

Depression is a critical intellectual fitness situation impacting hundreds of thousands worldwide. Its complicated and multifaceted nature makes it hard to diagnose and deal effectively. Traditional diagnostic strategies frequently depend on medical reviews and self-pronounced signs and symptoms, which may be prompted via way of means of subjectivity and bias. However, latest improvements in artificial intelligence (AI) and machine learning (ML) have opened new opportunities for enhancing the accuracy and performance of mental health detection. By leveraging multiple information sources [7] which includes wearable device data, medical data, social media posts [8], and self-pronounced questionnaires , researchers can expand strong methods figuring out mental well-being at risks early and accurately.

This study makes a specialty of growing an AI-pushed framework to deal with mental health concerns. Depression signs and symptoms may be diagnosed through multiple ways, consisting of persons' behavioral patterns, physiological signals, and textual content etc. To build an effective and powerful mental health detection system, requires the integration of both multimodal [9] and multilingual data .

- Social media provides valuable insights into users' feelings and mental health through posts, comments, and interactions.
- Wearable gadgets offer real-time physiological data, such as sleep patterns and heart rate, which may indicate depressive symptoms.
- Clinical data provide a proper medical history for assessing mental health conditions.
- Self-reported questionnaires offer subjective perspectives on emotional well-being.

Linguistic and cultural diversity pose significant challenges in diagnosing mental health issues. Many existing methods are limited to English-language data, reducing their effectiveness for regional speakers.Multilingual Natural Language Processing (NLP) techniques, such as cross-lingual transfer learning and multilingual embeddings, enable models to analyze text across different languages [4].A multilingual approach ensures inclusivity and broadens the applicability of AI-driven mental health assessments.

Ensemble learning, an effective Machine Learning(ML) [10] technique, combines a couple of techniques to enhance prediction of accuracy and robustness. Traditional single-version processes usually deal with problems like records noise, bias, and over-fitting. By using ensemble strategies [23] consisting of stacking, boosting, and bagging, this study aims to create a greater dependable and generalizable mental well-being prediction version. Stacking integrates predictions from a couple of base fashions the usage of a meta-version, even as boosting iteratively improves susceptible inexperienced persons via ways of means that specialize in misclassified instances. Bagging reduces variance via means of aggregating predictions from models trained from multiple datasets.

Ensemble learning additionally allows the combination of multimodal records for mental well-being detection. For example, combining physiological records from wearables with sentiment evaluation from social media permits a greater complete evaluation of intellectual health. Incorporating scientific records in enhances model accuracy and interpretability. The purpose is to leverage the strengths of diverse ML strategies to create a strong model for prediction of any mental health risk.

A key goal of this study is to enhance the performance, resilience, and generalizability of the mental well-being prediction version. Common demanding situations in ML, consisting of over-fitting, record imbalance, and poor generalization to new scenarios, might be addressed through optimization

strategies like characteristic choice, cross-validation, and hyperparameter tuning. Hyperparameter tuning [5] includes systematically adjusting version parameters to optimize performance, even as characteristic choice identifies the maximum applicable records attributes to enhance interpretability and decrease computational complexity. Cross-validation guarantees the version is skilled on numerous records subsets, improving its potential to generalize.

Additionally, multilingual adaptability [3] is critical, especially for textual content-primarily based totally depression detection. Techniques consisting of switch mastering with pre-skilled multilingual transformers (e.g., mBERT, XLM-R) can be explored to enhance the version's potential to manner textual content in other regional languages. By improving the version's robustness and adaptability, this study aims to create a fairly powerful system for correct prediction throughout numerous populations.

Mental health risk detection alone is not enough it is also important to offer customized guidance and uplifting support to individuals vulnerable to mental health challenges. This study aims to create a complete framework based on AI that combines mental well-being detection with relevant mental health interventions. This framework will consist of the extensions for data gathering, pre-processing, model training, prediction generation and advice. According to the severity of the diagnosis [16], the device suggests different interventions which may include mindfulness exercises, occupational therapy, self-help or online support programs. The advice device can be designed to give personal advice according to the person's information and behavioral patterns. The framework also implements circuitous interfaces for web and mobile, enabling instant feedback and evaluation of cognitive capabilities; making users extra focused to develop their intellectual thinking capacity. Security measures such as data encryption and anonymization can be employed to safeguard user privacy.

This Study propose a novel AI-based depression prediction framework that leverages multimodal [20] and multilingual information and so bridges the limitations of a uni-modal, unilingual worldview to improve depression prediction. This work proposes a device that utilizes multiple features extraction using the ensemble learning [1] for performance optimization, which extracts intellectual capacity comparison from multilingual data. Moreover, the fact that the personalized guidance system makes sure that they get a helping hand according to their mental health status helps them a great deal. It increases the ability to detect mental health problems early and intervene in order to increase better well-being and outcome via the findings of these studies.

2 Literature Review

Analyzing and recommending tools for depression prediction. The rise in mental health disorders has made early detection and timely intervention pivotal in improving patient outcomes. AI in this field can make big impacts from automating diagnostic procedures to enhance the accuracy of predictions to customizing treatment recommendations. In addition Machine Learning (ML), Deep Learning (DL), and Large Language Models (LLMs) and their hybrids and privacy-preserving AI have also been integrated into these systems which have made them powerful. Some of these technologies are combined and used to enhance the accuracy, efficiency, and scalability of mental health solutions.

2.1 Machine Learning Approaches

Traditional models have long been used in the prediction of mental health, including depression classification. Logistic Regression (LR): LR is one of the simplest classification algorithms available and is easy to implement and interpret, however its effectiveness is limited when modelling more complicated non-linear data patterns [2].Some features of LR make it a popular choice in preliminary research. On the other hand, SVM works wonders when you have most of the classes and examples, as they identify the right hyperplanes. However, their dependency on meticulous parameter tuning increases complexity, especially for larger datasets [15]. Random Forest (RF), is an ensemble method which is based on decision trees that effectively handles the non-linear data by aggregating multiple tree output.This makes it a strong choice for mental well-being detection or prediction; however, it requires very high computational resources. [10]. Gradient Boosting techniques, including XGBoost and Light-GBM, are well-known for their strong predictive capabilities and are frequently employed in mental health detection. These methods improve accuracy by sequentially building trees, but risk overfitting without proper tuning, potentially compromising real-world effectiveness [11]. Kumar et al. [20] introduced a hybrid framework that combines traditional machine learning models with deep learning, demonstrating that ensemble strategies can significantly enhance the outcomes of mental health predictions. By combining the strengths of traditional and advanced approaches, these hybrid systems deliver more adaptable and precise results, better suited to the complexities of mental health data.

2.2 Deep Learning-Based Models

Deep learning has transformed mental health like depression, anxiety etc. by leveraging its capacity to extract hierarchical features directly from raw data [26], particularly in image and text-based applications. Convolutional Neural Networks (CNNs) have demonstrated robust performance in image-based depression detection, such as analyzing facial expressions. By identifying spatial patterns in facial signs and emotional indicators, CNNs can detect early signs of mental health risks, often before individuals seek any professional help [23]. These models outperform at recognizing minute changes in facial expressions that may signal emotional distress, offering valuable diagnostic insights. For sequential data, such as text from social media posts or patient journals, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are commonly used. These model excels at understanding pattern over time ,help detecting mood shifts, negative expression or reduced social interactions, enabling them to identify behavioral patterns associated with depression [13]. However, these models are resource intensive and may encounter challenges like vanishing gradients, which hinder their ability to model long-term dependencies effectively [14]. To overcome these limitations, Zhang et al. [18] introduced a hybrid CNN-RNN model that combines the strengths of both architectures. The RNN

processes sequential data, like text from conversations or posts while CNN component extracts features from image data, such as facial expressions. This results as improved accuracy of mental health detection, especially when multimodal data sources such as combined text and image inputs are used to provide a better assessment of an individual's emotional state.

2.3 NLP Models for Depression Analysis

Natural Language Processing (NLP) have significantly improved the ability to analyze textual indicators of depression. BERT (Bidirectional Encoder Representations from Transformers) is commonly used for sentiment analysis, demonstrating success in identifying negative emotions and depressive language [13]. However, BERT faces challenges in maintaining long-term context, which limits its capacity to fully grasp the evolving nature of human emotions over time. RoBERTa, an enhanced version of BERT, performs better in fine-tuning tasks,making it more effective for identifying mental health risk indicators in specific datasets. In dynamic social media conversations [14], where context and sentiment shift, its improved training process is beneficial in detecting depressive signs effectively. Additionally, Miller et al. [21] highlight the significance of integrating attention mechanisms in deep learning models for depression detection. These mechanisms allow the model to focus on critical keywords or phrases, enhancing its ability to detect subtle signs of depression that may otherwise be missed, improving both sensitivity and specificity in the process.

Table 1: Models for depression prediction and recommendation model

Category	**Model/Technique**	**Description**	**Advantages**	**Limitations**	**Ref.**
Machine Learning (ML)	Logistic Regression (LR)	A baseline classifier for binary depression detection.	Simple & interpretable.	Poor performance on complex data.	[2]
	Random Forest (RF)	Ensemble learning technique using decision trees.	Handles non-linearity well.	Computationally expensive.	[10]
	Support Vector Machine (SVM)	Finds optimal hyperplanes for classification.	Works well with small datasets.	Requires careful parameter tuning.	[15]
	Gradient Boosting (XGBoost, LightGBM)	Boosted decision trees for high-performance predictions.	High accuracy with structured data.	Overfitting risk.	[11]

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Category	**Model/Technique**	**Description**	**Advantages**	**Limitations**	**Ref.**
Deep Learning (DL)	Convolutional Neural Networks (CNNs)	Extracts spatial patterns for image-based depression detection.	Effective for facial expression analysis.	Needs large labeled datasets.	[23]
	Recurrent Neural Networks (RNNs)	Processes sequential depression-related data (e.g., tweets).	Captures temporal dependencies.	Vanishing gradient issue.	[13]
	Long Short-Term Memory (LSTM)	Enhanced RNN variant for long-term dependencies.	Works well for text-based depression tracking.	Computationally expensive.	[14]
Hybrid & Ensemble Learning	Stacking Ensemble	Combines multiple classifiers (e.g., RF + SVM + LSTM).	Improves prediction accuracy.	Complex implementation.	[23]
	Attention-LSTM	Uses attention mechanisms for sequence-based depression analysis.	High performance in social media text classification.	Requires high computational resources.	[13]
NLP Models	BERT	Pretrained transformer model for depression text analysis.	Context-aware NLP processing.	Struggles with long-term context tracking.	[13]
	RoBERTa	Optimized BERT with better sentiment analysis capabilities.	High accuracy in depression classification.	Requires extensive fine-tuning.	[14]

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Category	Model/Technique	Description	Advantages	Limitations	Ref.
Recommendation Models	Collaborative Filtering (CF)	Recommends therapy resources based on similar user preferences.	Personalized recommendations.	Cold start problem.	[16]
	Content-Based Filtering (CBF)	Suggests mental health resources based on past behavior.	Works well with limited data.	Limited diversity in recommendations.	[16]
	Hybrid Recommendation	Combines CF & CBF for enhanced personalization.	Adaptive and user-specific recommendations.	Computationally expensive.	[10]

2.4 Hybrid and Ensemble Learning Approaches

Mental health prediction systems accuracy and reliability of mental health prediction can be improved using hybrid and ensemble learning techniques by combining multiple models. By combining the predictions from multiple classifiers, ensemble methods can mitigate the limitations of individual models will lead to overall better performance. Stacking ensembles, which integrate classifiers like Random Forest, SVM, and LSTM, have been shown to significantly enhance accuracy [23]. These ensembles take advantage of the unique strengths of each model, resulting in more dependable and precise predictions. The Attention-LSTM model represents another promising hybrid approach for depression detection. By focusing key features in sequential data, Attention-LSTM enhances the model's ability to identify patterns related to depression, such as negative emotions or emotional instability over time [13]. However, Attention-LSTM models may include excessive computations and may require significant resources for effective training. Gupta et al. [24] created a more robust depression detection system have applied ensemble learning to merge the strengths of deep learning and traditional machine learning models. The challenges posed by mental health data, which is often noisy, imbalanced, and high-dimensional is effectively addressed by this method

2.5 Recommendation Models for Mental Health Support

Along with mental health prediction systems, recommendation models also play a crucial role in providing personalized mental health interventions. These systems can recommend self-help tools ,therapy resources or support groups based on the user's mental health status and preferences. Collaborative Filtering (CF) and Content-Based Filtering (CBF) are the two most commonly used recommendation techniques. CF systems recommend resources based on the similarities between users often suffers from the cold start problem, where due to the lack of historical data new users or resources cannot be recommended effectively [16]. To address this issue, CBF recommends resources based on individual

user profiles, considering their past behavior, preferences, and engagement. This solves the cold start problem, however CBF lacks diversity in its recommendations, as it only suggests items that are similar to the user's past behavior [16]. A hybrid recommendation approach, which combines CF and CBF, was proposed to offer more personalized suggestions by integrating both behavioral and profile-based data. This method enhances personalization, but it comes with increased computational complexity and requires careful balancing to ensure that the recommendations remain diverse and accurate [10]. Sharma et al. [19] have successfully applied deep learning-based hybrid systems to personalize mental health interventions, integrating user behavior and profiles to provide tailored recommendations that meet individual needs.

3 Research Gap

- Existing studies focus mainly on social media data (Reddit, Twitter, etc.), but lack integration with wearable sensor data, self-reports, and clinical records for a more comprehensive depression risk assessment.
- Current models are trained on limited and region-specific datasets, failing to account for diverse demographics, gender differences, and cultural variations in depression symptoms.
- Lack of research on hybrid models that effectively combine traditional ML techniques with Deep Learning and Natural Language Processing for improved prediction.
- Recent studies mainly classify depression at a single time point rather than tracking mental health deterioration over time, limiting their ability to predict future risk.

4 Study Hypothesis

H1 : Integrating multimodal and multilingual data will improve depression detection by capturing diverse behavioral patterns and enhancing model applicability across populations.

H2 : Developing a deep ensemble model that integrates multiple deep learning architectures will enhance the overall performance of depression detection by leveraging the strengths of different models.

H3 : Systematic hyper-parameter tuning of the developed deep learning models will optimize their performance, leading to improved prediction accuracy and efficiency.

H4 : A deep ensemble model combining multiple architectures will reduce prediction errors and overfitting, leading to enhanced accuracy and generalization in depression detection.

5 Aims & Objective

- To integrate multimodal and multilingual data for depression detection and prediction.
- To develop a deep ensemble model that integrates multiple deep learning architectures.
- To optimize the developed model through hyperparameter tuning to achieve enhanced performance.
- To develop a comprehensive framework for depression detection and personalized mental health recommendations to improve early diagnosis and intervention.

6 Proposed Methodology

The proposed research methodology will focus on developing a deep ensemble model that combines both multimodal and multilingual data, and will also integrate these datasets for the prediction of mental health wellness more accurately. In addition to diagnosing depression, the system aims to provide personalized mental health recommendations. The strategy includes the following steps:

6.1 Data Collection

A diverse and comprehensive dataset is essential to accurately detect any mental health risks. Data will be collected from multiple sources to capture different aspects of an individual's mental health.Wearable device data will be collected from fitness trackers and smartwatches to monitor physiological signals such as heart rate variability, sleep patterns, and daily activity levels, which are key indicators of mental health. Social media data will be gathered from platforms like twitter, reddit etc. where text-based posts,images containing texts, comments, and interactions can provide insights into social behaviors, emotional states, and potential depressive tendencies. Questionnaire data will be derived from structured self-assessment surveys such as PHQ-9 [**?**] and GAD-7, which are widely used in psychological evaluations to quantify depression symptom. Clinical data will include medical records, psychological assessments, and diagnostic reports obtained from mental health professionals, providing validated indicators of depression.

6.2 Language Identification and Translation

Data will be collected from multilingual sources, before processing we need to standardize text-based inputs. To determine the original text language, each entry will undergo language detection. Any text other than English will be translated using Google Translator API to ensure consistency in the dataset. This step is critical for analyzing social media posts and questionnaire responses effectively, as mental health risks must be clearly interpreted across different linguistic contexts

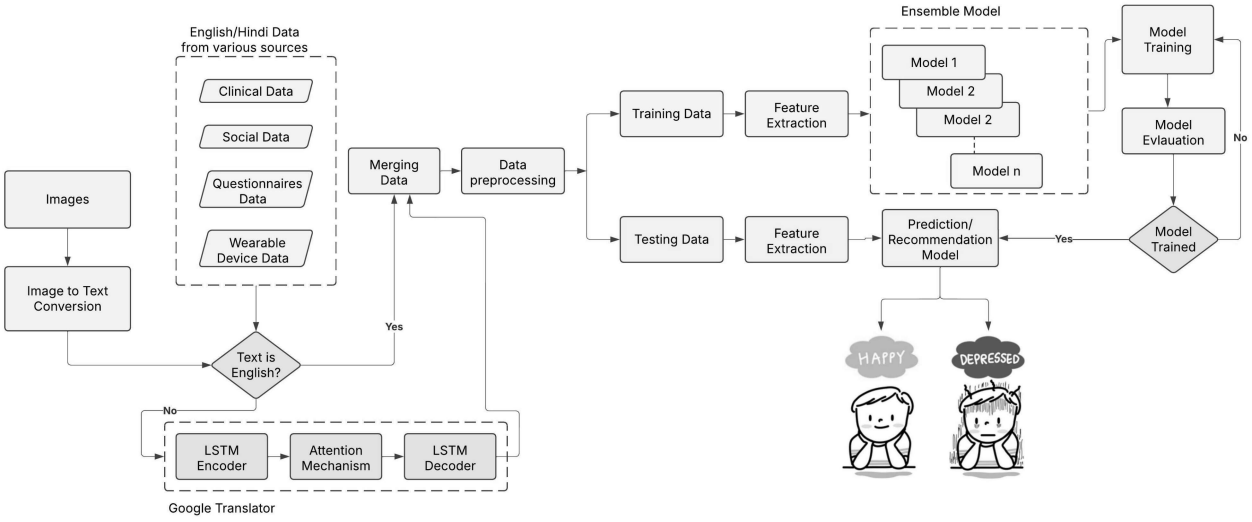

Figure 1: Process flow for Depression Detection and Recommendation System

6.3 Data Merging and Pre-processing

After collecting data from various sources, they must be integrated into a single dataset while ensuring compatibility and consistency of the data. Data integration will involve linking individual-level data from different sources while maintaining privacy through anonymization techniques. Text pre-processing will be performed on social media and questionnaire responses, including tokenization, stop-word removal, lemmatization, and stemming, to refine the text for sentiment analysis and topic modeling. Numerical data pre-processing will involve normalizing and standardizing wearable data to maintain consistency between individuals. The handling of missing values will be done using statistical imputation techniques, while feature selection using Principal Component Analysis (PCA) and correlation analysis will be employed to retain only the most relevant features for model training.

6.4 Model Training using Deep Ensemble Model

To achieve high accuracy and robustness in depression detection, a deep ensemble model will be used. This approach will leverage multiple base models that specialize in different types of data. CNN-LSTM architectures will be used for wearable data analysis to capture sequential patterns in physiological signals. Transformer-based NLP models such as BERT and RoBERTa will be employed for analyzing text from social media and questionnaires, enabling context-aware sentiment analysis. Fully Connected Neural Networks (FCNNs) will process structured clinical and questionnaire data. These models will be combined using ensemble learning techniques, such as stacking or weighted averaging, to maximize predictive performance. Attention mechanisms will be incorporated to highlight the most relevant features contributing to depression detection. Optimization techniques, including Bayesian hyperparameter tuning, dropout regularization, and batch normalization, will be applied to improve model generalization and prevent over-fitting.

6.5 Model Evaluation

Model evaluation will be conducted thoroughly to ensure effectiveness and reliability of the proposed model. Performance metrics such as accuracy, precision, recall, and F1-score will be used to measure classification performance, while the Area Under the Curve - Receiver Operating Characteristic (AUC-ROC) metric will assess the model's ability to distinguish between depressed and non-depressed person. Cross-validation using K-fold techniques will be performed to evaluate model stability across different subsets of data.

6.6 Model Testing

The final model will undergo rigorous testing on unseen data to validate its real-world applicability. External validation will be performed using datasets from different sources to assess the generalizability of the model. Deployment feasibility will be analyzed by evaluating model inference time and computational efficiency, ensuring its practical usability in academic or clinical settings. To address privacy concerns, techniques such as federated learning may be considered for decentralized training without exposing sensitive user data.

7 Expected Results/Outcomes

- Existing depression detection models often rely on single-modal data (e.g., text or speech), limiting their effectiveness in capturing comprehensive behavioral patterns and also lack of multilingual support
- Current models struggle with overfitting, making them less effective in generalizing to unseen data, leading to poor performance in real-world applications, where the data varies significantly from training sets.
- Current depression detection models are constrained by default or manually chosen hyperparameters, which might not be optimal for specific datasets resulting in inefficiencies and performance.
- Recent studies primarily classify depression at a single point in time, rather than tracking mental health deterioration over time, limiting their ability to predict mental health risks in the future and accurately monitor the progression of depression.

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